GMR
The Original

FROM PREDICTION TO PRACTICE: A BIBLIOMETRIC AND SYSTEMATIC REVIEW OF ARTIFICIAL INTELLIGENCE IN PRECISION HORTICULTURE—FIELD VALIDATION, CROSS-CROP GENERALIZABILITY AND DECISION-SUPPORT READINESS

Dr. Abhilash Mishra[1*], Dr. V.Madan Mohan Rao[2], Er. Sandipkumar G. Patel[3], Mr. Abinash Mohanty[4], Hema[5], Pragya Shrivastava[6], Khati Malo[7], Rakesh Kumar[8], Dr. Dhara Suthar[9], Miss Bhawna Panda[10] and Naval Kishore Meena[11]

[1]Guest Faculty, Department of Fruit Science, Mahatma Gandhi Udyanikee Evam Vanikee Vishwavidyalaya, Durg, C.G.
[2]Head of Department, Department of Botany and Horticulture, Government Degree College, Chintalapudi Eluru, (Adikavi Nannayya University, Rajahmahendravaram, Ap).
[3]Assistant Professor (Comp.Science), Department of Basic Sciences, ASPEE College of Horticulture, Navsari Agriculture University.
[4]Ph.D. Research Scholar, Department of Environmental Science, Manipur International University.
[5]Ph.D. Scholar, Department- School of Agriculture, Uttaranchal University, Dehradun, Uttarakhand.
[6]Research Scholar, Department of Fruit Science, Mahatma Gandhi Udyanikee Evam Vanikee Vishwavidyalaya, Sankara, Patan, Durg (C.G.), 491111.
[7,8] Ph.D. Scholar, Division of Vegetable Science, SKUAST- Jammu, Sher e Kashmir University of Agricultural Science and Technology Jammu- Chatha, 180009.
[9]Assistant Professor, Department of Horticulture, College of Agriculture, Parul University.
[10]Assistant Professor, Department of Fruit Science, MGUVV-College of Horticulture and Research Station, Raigarh (Chhattisgarh) Pin 496001. (Mahatma Gandhi Udyanikee Evam Vanikee Vishwavidyalaya, Durg (C.G.)
[11]Ph.D. Scholar, Department of Horticulture (Fruit Science), Rajasthan College of Agriculture, MPUAT, Udaipur-313001, Rajasthan.
***Corresponding Author**: Dr. Abhilash Mishra, E-mail: abhilashmishra158@gmail.com

ABSTRACT
Artificial intelligence is increasing the ability to monitor, analyse, and operate horticultural production offering opportunities in crop monitoring, resource allocation, and production efficiency. However, predictive performance in controlled experimental settings may not lead to reliable agronomic results or valuable into practice. This review examines three interconnected questions in the walk of transition from algorithmic development to operations: if intelligent systems are resilient in the face of varied production conditions, if knowledge and learning transfer effectively across crops and environments, and if model outputs provide defensible information management. Research examples of disease diagnostic, orchard monitoring, greenhouse control, and robotic harvesting enable us to put advances in context by considering current capabilities, methodological limits and practical adoption. There is also a focus on dataset representativeness, independent validation, environmental variability, uncertainty estimation and agronomic knowledge integration into decision processes. We outline a reproducible framework for the following bibliometric and systematic analysis, openly describing methods of literature search, study selection, evidence extraction and critical appraisal without claiming an actual database census. What is more important than individual metrics of predictive accuracy is that the predictor can meet a number of practical readiness requirements: consistent performance in all relevant settings, explicit communication of uncertainty of estimates, biological constraints, operational constraints and demonstrated benefits for growers. Future research should focus on transferable learning, field testing designs to avoid bias, clarity in its advice and comparing with current practices. Ultimately, the real test of progress in horticultural artificial intelligence is reliable decisions and tangible gains in productivity, resource efficiency and operational feasibility.

KEYWORDS: Artificial intelligence; horticultural production; cross-crop transfer learning; independent validation; uncertainty estimation; decision support; operational readiness.

1. INTRODUCTION
Precision horticulture seeks to match management with variation among plants, production zones, and developmental stages. Its importance is due to the biological and commercial diversity of fruits, vegetables, flowers, and nursery crops. In one enterprise, differences in canopy architecture, irrigation demand, harvest maturity, and market specifications can call for separate platforms (Baiardi *et al*., 2026). Artificial intelligence can integrate observations made by cameras, environmental sensors, and production records into decision-making. But the objective of interest is often not prediction alone. The growers have to choose when to irrigate, where to search, which fruits to harvest, and whether intervention costs are worthwhile. Consequently, evaluating horticultural intelligence requires attention to the complete pathway linking measurement, interpretation, action, and consequences under the conditions of commercial production (Chaudhary *et al*., 2025).
Horticulture is more complicated than ordinary similar year entry fields of crops. Below are perennial orchard fruits that

provide maintenance of pruning effects, rootstock choice, previous crop load, and accumulated stress, year to year. Vegetable production involves repeated harvests, rapid developmental changes, and strong quality response to lack of water or nutrient availability. Protected cultivation presents a more controlled environment but introduces coupled decisions about heating, ventilation, lighting, carbon dioxide, and fertigation (Chen *et al*., 2025). Ornaments typically have different species diversity aesthetic grades of the range of standardized targets are more complicated. The differences make treating horticulture as a single predictive problem very difficult. A transferable analytical approach must be able to determine which processes can be shared, and which necessarily involve crop knowledge, local calibration, or a completely different management objective (Scalisi *et al*., 2024).



Figure 1. Integration of Artificial Intelligence and Smart Technologies in Precision Horticulture

This review is structured around three dimensions. Field validation is whether the method works in a realistic production setting, meaning: representative plants, environments, operators and equipment. Cross-crop generalizability is whether the knowledge gained is still relevant when the target crop is switched, especially if the biology and management practices of that metabolization differ from those represented during development (Hossen *et al*., 2025). Decision-support readiness is whether the resulting knowledge facilitates a timely, possible, and responsible action. These dimensions can be intertwined yet they can't replace each other. Outdoor performances may stay good for one trait but not across against other traits. The adaptable model may be unsuitable for prevention. A realistic advisory may work by using baseline models demonstrated on solid agronomy, reliable infrastructure, and suitable human management (Benfenati *et al*., 2025).

2. REVIEW SCOPE AND METHODOLOGICAL FOUNDATION

2.1. Research Questions and Manuscript Status

The review discusses research trends where artificial intelligence meets horticultural production for readying for move from technical demonstration to management use. Its guiding questions revolve around the focus of research attention, the validity of validation, the strength of transfer assertions, end-user operating conditions and when a technology is ready to be launched for field deployment. Similarities with agricultural machine learning are noted only when they are directly relevant to an application in horticulture. Postharvest technologies can also be relevant to postharvest (for example, grading, storage, and market information that impact production decisions) (Kaur and Watson, 2024). It integrates published observations and methodological recommendations and conceptual proposals. This is relevant because an appealing evaluation framework is not itself proof that existing systems meet its requirements or reap benefits across the entire gamut of horticultural enterprises (Ibnat *et al*., 2026).

The present manuscript is a research-grounded critical synthesis with a proposed bibliometric and systematic review protocol, rather than a completed original bibliometric investigation. Targeted searches identified relevant primary studies, but a complete database export, documented deduplication, independent screening, and formal study appraisal was not performed. These analyses will need to be completed before submission under an umbrella such as a completed bibliometric and systematic review. This methodological prerequisite shields the possibility of case narratives being reported as findings without having a standardized process in place and creating a transparent path from this to a reproducible research

contribution of a final manuscript where evidence is verifiable and conclusions are justifiably supported (Donthu *et al*., 2021).

2.2. Search Strategy and Evidence Selection

A definitive search should combine multidisciplinary indexing with the use of agricultural and engineering databases that cover agronomic experiments and computer science contributions (Bramer *et al*., 2017). Search concepts should include horticultural commodities, artificial intelligence methods, precision management tasks, and production environments. Crop names are key because relevant papers may mention, for example, apple, tomato, cucumber, or grapevine without using horticulture. Validation terminology should not be required by searches, because it may accidentally omit studies with limited validation and distort the results of maturity level and technological readiness evaluations. The protocol should define coverage dates, languages, document types, and the final search date. Exact database queries and exported records should be captured in case another team later wishes to reconstruct the evidence base to assess the effects of different search strategies (Rethlefsen *et al*., 2021).

Eligibility should be empirical studies involving identifiable horticultural crops and explicitly computational task, either about production or management. The cognitive discussion can be advanced with studies, but it must be avoided in quantitative summaries of demonstrated performance. Each paper should provide a record of coding that involves the crop, cultivar, production setting, geographic information, sensing modality, structuring of sample, model class, comparator, design for validation, and operational outcomes (Page *et al*., 2021). Records should be screened by independent reviewers and disagreements resolved by applying pre-established guidelines. Duplicate publication of the same results on multiple papers need be related, to avoid double-rater weighting. Reports should clearly state if a study was irrelevant in terms of many not reporting needed information or if key information was missing for discussion of that study. Missing methodological details should remain visible as uncertainty rather than being silently interpreted as evidence of adequate practice (Moons *et al*., 2025).

3. BIBLIOMETRIC PERSPECTIVE: MAPPING ATTENTION AND EVIDENCE

Published bibliometric work supplies context, but replaces that with its own definition not horticulture-specific corpus. In smart agriculture, a study of operations research and decision support in smart agriculture found 1,305 Scopus records from 2000 to 2022 (Sahar *et al*., 2026). Its broad scope showcases the ability of mapping to connect algorithms with resource allocation and management patterns. However, its publication counts and thematic structure are not evidence of precision horticulture. Bibliometrics is a measure of the organisation of research for the proposed review, systematic appraisal is the standard to decide evidential strength Use of citation counts is a function of visibility, publication age and database coverage which affect its impact on agronomic effectivity. We can link every mapped paper with its validation design with the purpose of exploring not only its intellectual influence but also making it useful for practical validation (Yousaf *et al*., 2023; Marzi *et al*., 2025).

Research visibility should also be monitored in relation to horticultural production diversity. More frequently studied crops should feature datasets, research infrastructure or market dynamics that can affect investment decisions. Few vegetables, tropical fruits, ornamentals and mixed production systems may need specialized sensing and management solutions (Shawon *et al*., 2026). Neither regional dominance nor crop imbalance can be measured without a specific corpus. Then, rather than so-called inherent assumptions, interpret the results through a bibliometric lens. Tying the country affiliation with the site of experimental validation is dangerous, since international collaborations could work with datasets from other sites. Having a record of both research origin and deployment setting would allow us to better understand whose production conditions are reflected in the evidence (Shawon *et al*., 2026).

4. APPLICATION EVIDENCE: FROM CROP OBSERVATION TO INTERVENTION

4.1. Sensing and Biological Interpretation

Application areas also usually start with the computational task of converting heterogeneous observations into biologically relevant variables. Visible imagery can capture fruit appearance and canopy structure, whereas thermal and spectral measurements can add information regarding temperature, pigments, or water relations. Environmental sensors describe the conditions under which these observations are taken (Murphy *et al*., 2024). Integration is only possible when measurements are aligned in space, time, and biological scale. A leaf image, an orchard weather station and a satellite pixel are not associated to the same sampling unit. Models must account for information about measurement support and uncertainty. Otherwise, apparent gains from combining data may reflect coincidental correlations rather than an improved understanding of the plant processes relevant to management (Gao *et al*., 2024).

4.2. Disease Recognition and Diagnostic Reliability

Disease recognition illustrates both the promise and the limits of image classification. An influential Plant Village study reported 99.35% accuracy on held-out images from its controlled collection, but approximately 31% accuracy on two small external image sets. Those external sets were obtained from online sources and should not be described as prospective commercial field trials. Nevertheless, the contrast demonstrates how strongly performance can depend on image distribution (Jelali, 2024). Backgrounds, lighting, symptom presentation, and acquisition practices may change outside development data. The practical lesson is specific: success on a controlled benchmark establishes technical feasibility, while reliable field diagnosis requires evaluation against representative symptoms and confounding conditions encountered during actual scouting and subsequent advisory use (Moupojou *et al*., 2023).

Diagnostic usefulness also depends on permitted inferences of the model. The exact same type of discoloration may also be caused by pathogens, nutritional deficiency, water stress, chemical injury, or senescence. An image classifier trained on a closed list of diseases might label an unfamiliar condition with the most comparable disease known to it even when no diagnosis is appropriate (Shafay *et al*., 2025). Horticultural decision support systems should be designed to deal with uncertain, mixed, and unrecognised cases with escalation to specialist assessment or laboratory confirmation where appropriate. Rather a classification may influence disease severity, proportion of plants affected, phenological development stage, and weather suitability whether it is required for management or a categorical name alone. As such, evaluation should measure whether the system assists with scouting priorities and diagnostic workflows, without presupposing that visual recognition alone justifies treatment (George *et al*., 2025).

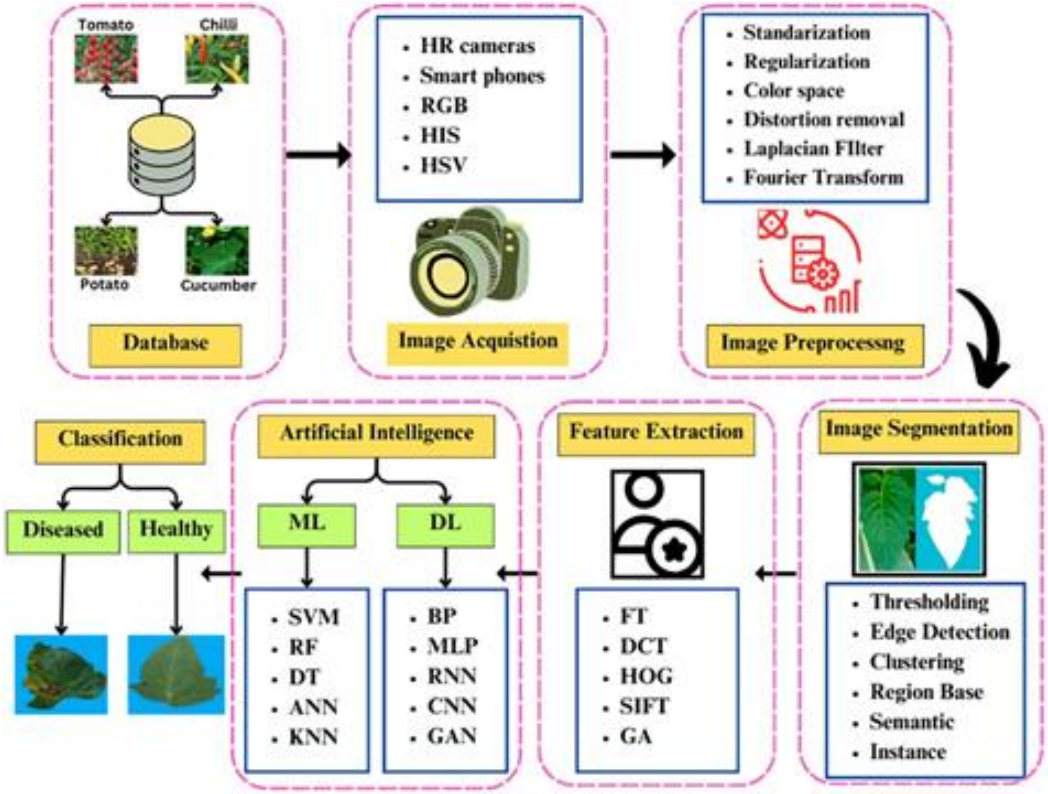


Figure 2. Artificial Intelligence Framework for Image Processing and Disease Classification in Vegetable Crops

Source- Jafar *et al*., 2024

4.3. Fruit Detection and Yield Forecasting

Fruit detection provides another important foundation, supporting inventory, maturity assessment, and robotic perception. Deep Fruits broke ground where deep neural detection methods were applied to fruit imagery, allowing us to move past trained features. Yet recognizing visible fruit remains distinct from estimating the entire crop (Pai *et al*., 2025). Cues such as occlusion, overlapping clusters, reflective surfaces, fruit colour and changing illumination can affect what cameras can capture. A model is suitable for clearly visible objects but may not work as well, when applied to dense commercial canopies. These studies should report on visibility conditions and the definition of a detectable target. In this way, growers and engineers can assess whether the success is merely common crop structure or if it was achieved using limited imaging settings that may not be easy to replicate (Hayat *et al*., 2026).

Yield estimation must link visible detections to biologically complete and commercially relevant totals. Aerial imagery has been used for orchard research to combine detected apples with regression to correct for fruit lost to the camera. Video approaches also demand tracking to avoid over-counting the same fruit (Valente, 2022). These strategies highlight that yield prediction is conditional on assumptions about visibility, identity, fruit size, sampling coverage and mass conversion. Error assessment should be done on a management scale such as individual trees or harvest blocks, instead of simply image level. Forecast timing is of equal import: a quick estimation at least a week before the expected harvest may be of little or no use to people earlier making decisions on labour contracting, storage and market commitments that weeks in advance (Neupane *et al*., 2023).

4.4. Irrigation and Nutrient Management

Water management must move from the stress estimation approach to one that makes restricted irrigation decisions, defined by soil, roots, weather, and infrastructure. Thermal observations, soil moisture records, and plant samples can provide independent evidence, but they run orthogonal to spatial and temporal response processes. A warm canopy may represent variation in the atmospheric demand and water availability, and conversely, a soil sensor posts as limited volume of soil as

monitored (Nikolaou *et al*., 2020). Predictive model results should then be assessed against a range of scheduling options, including water balance techniques, sensor thresholds and established, reputable methods. Key metrics for field evaluation are applied water, marketable yield, fruit quality, and relevant carryover effects. Moreover, sensor-based irrigation resulting benefits cannot be automatically considered as artificial intelligence unless data-driven analytical contributions are isolated and validated (Bounajra *et al*., 2024).

Nutrient management presents a related but distinct inference problem because visible or spectral symptoms are rarely specific to one nutrient. Leaf age, cultivar, water status, disease and illumination all can change the same optical indicators that are measured to estimate nutritional condition (Zhang *et al*., 2026). Systems used include plant observations, root-zone measurements, fertilizer history and appropriate tissue or solution analyses (Najdenko *et al*., 2024). In fertigation, recommendations will have to consider concentration, delivery volume, nutrient interactions, and drainage. After all, predicting leaf nitrogen levels does not answer whether a recommended fertilizer adjustment helps improve crop performance. Such validation should gain traction with intervention through nutrient use, yield, quality, and losses to the biosphere and environment. Such evaluation is a way to distinguish information gained through monitoring from agronomically controlled nutritional supply over time (Polder *et al*., 2024).

4.5. Autonomous Greenhouse Management

Protected cultivation offers unusual and abundant opportunities to assay the complete sensing-to-action pathway in terms of environmental control and production outcomes concurrently (Adabara *et al*., 2026). In an autonomous greenhouse experiment, five teams remotely managed cucumber crops in separate compartments over four months, with performance compared against a manually managed reference. One team exceeded that reference, demonstrating that algorithm-guided control can deliver measurable production value under specified conditions (Hemming *et al*., 2019). It does not mean these are all better than other ways of running greenhouses or climates. The relevance is telling operational management rather than single predictions. You have to pay attention to the various forces on these experiments: compartment replication, shared infrastructure, human interventions, how this works up until your same process outcompetes when confronting the different biological and economic conditions (Elings *et al*., 2019).

Autonomous greenhouse work on dwarf tomato extended experimentation to a crop setup with different growth and management characteristics. It's great evidence that autonomous farming research is broader than most will realise. But a different approach may have to be taken when you get around to testing the same approach on cucumber instead of tomato. Controllers may need to be redesigned, retrained, or provided with other crop parameters. The true transfer test then is to find out what components are constant, and what ones you will need more information about. Greenhouse trials should also include data on manual crop work and an automated climate control, as environmental autonomy does not imply full labour autonomy. This is important for identifying the limitations of the demonstrated capabilities and the still required steps towards fully autonomous production (Maree *et al*., 2025).

4.6. Robotic Harvesting and Marketable Quality

Robotic harvesting exposes the consequences of errors that image benchmarks cannot reflect (Gong *et al*., 2022). A robot must find a target, estimate its pose, get to it without hitting anything, detach it well and then relocate it in a not too damaging manner. In a commercial greenhouse study of sweet pepper harvesting, success was significantly improved through simplification of crop conditions, highlighting the importance of physical accessibility in addition to perception (Lehnert *et al*., 2020). Results such as these support viewing crop structure and machine design as interacting parts of the production system. Evaluations of harvesting must include failed attempts, surplus/overripe produce, cycle time, interruptions, operator assistance. High-performance detector cannot keep up with non-robust detachment or long handling times, especially when fruit value is influenced by factors such as appearance and hardness due to post-harvest spoilage (Arad *et al*., 2020).

Quality assessment links production decisions to what buyers actually value. The models employ imaging and associated measurements to estimate size, colour, surface defects, firmness or soluble solids; however, the biological meaning of each particular target is different. External appearance is sometimes directly observed, but internal quality is usually associated with destructive or instrumented measurements through calibration (Chuquimarca *et al*., 2024). Destination, transport duration, storage conditions, and cultivar-specific maturity relationships should be considered in the recommendations for harvest. A grading model trained based on one commercial standard may not be appropriate for another market. Therefore, it is essential to describe how predictions affect product volume and value based on misclassification costs. This broader view helps prevent economically-important errors in premium classes or sensitive market segments from going unnoticed under an overall high grading accuracy metric (Akter *et al*., 2024).

5. FIELD VALIDATION: ESTABLISHING CREDIBLE PRODUCTION EVIDENCE

5.1. Matching Claims to Validation Design

Field evidence may be seen as a trail moving from retrospective datasets to prospective operational testing. The first stage of a model is that a model, you might give it stolen data, as long as you rate it as treated or untreated, it might not be an independent production data. In later stages are external farms or seasons, real-time use, and comparison of management outcomes (Ruder *et al*., 2026). Models are successively more mature with the following systematic steps to determine evidence maturity, but it does not signal that every project needs to try to get fully autonomous. Their careful use as a scouting aid may find use in a narrow sense. The only requirement is the stated capability meets evaluation. Authors must report whether they provide evidence of recognition, prediction, recommendation, intervention, or realized production benefit

in a specifically defined operating context (Amodio *et al*., 2026).

Data leakage is a major threat whenever observations share plants, locations, acquisition sessions, or temporal sequences. A model can encounter very similar scenes in the development and evaluation phases when nearby video frames are randomly used as training and testing examples. Similar problems can also be encountered when repeated recordings from one tree appear in both sets (Chansanam *et al*., 2026). Consequently, the number of images can overstate the true span of the experiment. Thus, splitting should follow its intended final product with either plant, block, farm, season or region as the boundaries for separation. The pre-processing, feature selection and hyperparameter tuning must also remain within development data. These protections are designed to ensure that the reported performance is a better estimate of how the model will perform on future data as opposed to when the dataset was assembled (Kapoor and Narayanan, 2023).

5.2. External Validity and Measurement Quality

External validation needs to disrupt the factors most likely to hamper submission. While testing on another season tests temporal stability, another farm brings management, soils, equipment and local climate differences. Neither alone establishes robustness to all relevant changes. Study designs should report what changed and what stayed the same, providing information about the sample transfer difficulty (Ahmad *et al*., 2023). When sample sizes allow, performance should be disaggregated across cultivar, growth stage, disease incidence, canopy density, and environmental context. It is more useful to show how much of the outcome deviates from the expected value, instead of only reporting an overall average. Confidence intervals should capture effects of clustered sampling, data from the same farm or production cycle is not the same as independent replications across environments (Wang *et al*., 2023).

Ground truth needs the same scrutiny because a model can't be evaluated more accurately than its reference measurements allow. Labels that rely on clinical judgment alone may be more interpretative, while harvest counts are prone to underestimation of fruit hidden or losses that happen after imaging. Water stress measurements vary depending on timing and biophysical context. Annotation procedures should assess the expertise, instruments, time, disagreement and precision of measurement. If the target is unknown, it should be treated as uncertain uncertainty, instead of a confirmed measurement represented by a bin. Appropriate evaluation metrics are essential as the measures of detection, counting, predicting, and the success of an intervention are different. When studies use the same word, accuracy for outcomes with incompatible definitions, denominators and practical implications for growers (Farjon and Edan, 2024).

5.3. Comparators and Agronomic Outcomes

Demonstrating agronomic benefit requires comparison to realistic alternatives rather than poorly designed baselines. An apple orchard case study comparing detection and counting methods found a slightly supervised approach produced better detection in all of but a few tested datasets, but deep learning did better in counting. Such task dependent result challenges one model family to outperform all others in an entire workflow (Johanson *et al*., 2024). Prospective management experiments should similarly compare systems with experienced growers, established advisory rules, or simpler statistical methods. Randomized blocks, matched sites, or phased implementation separates intervention effects from environmental differences. Outcomes should incorporate marketable production, quality, resource consumption, labour, and unintended consequences. This comparison must isolate the contribution reasonably attributable to a proposed decision process under realistic production conditions (Johanson *et al*., 2024).

6. CROSS-CROP GENERALIZABILITY: WHAT ACTUALLY TRANSFERS

6.1. Defining Transfer Beyond Software Reuse

Cross-crop generalizability must be defined more carefully than reuse of a software architecture. Training the same neural network for several crops separately just shows one can port methods, but it does not always mean learned knowledge can be transferred. Transfer can occur via frozen features, fine tuning, shared training, or adaptation by using target-crop observations. These approaches differ in data needs and should be reported separately (Tunio *et al*., 2024). A strong claim provides the source crop, target crop, available target information, unchanged model components, and achieved performance. The critical question is whether prior learning actually makes this task more or easier. Without this evaluation, plausible broad applications may hide repeated collection of data and rejection of algorithms for application to a range of horticultural production systems (Hossen *et al*., 2025).

Biological differences explain why transfer may work for some but not others components. Visual features describing edges or textures may be useful across crops, while relationships between canopy temperature and irrigation need depend on physiology and growing conditions. Fruit detection must accommodate differences in size, clustering, pigmentation, and background similarity. Harvesting stages also vary according to each crop’s maturity characteristics and market demands (Miranda *et al*., 2023). Models need to separate broadly useful representations from task-specific biological relationships. Only visual or botanical similarity is not enough to predict, which crops are similar two crops. A predictive hypothesis considers the underlying similarities (common mechanisms or common observables) and then evaluates stability when the new crop has new form, new management, and different environmental responses (Johri *et al*., 2024).

6.2. Evaluation Designs and Adaptation Costs

Leave-one-crop-out evaluation presents a relevant design for testing generalization beyond the crops represented. A model is trained on several crops and evaluated on a held-out crop, and the process move across relevant targets with repeats. However, this might result in varied results based on how the target labels and task definitions align. A disease category appearing only in the withheld crop, whereas recognizing a common symptom on a novel host represents a separate challenge (Fuentes *et al*., 2021). Consequently, benchmarks should differentiate between tasks common to all crops and truly

novel ones. They should also keep target-crop clues out of model selection. Combined measuring overall performance after transferring and the weakest target helps identify if overarching assertions rely on a handful of relatively easy transfers while leaving the approach most insipid in addressing any commercially significant crops (Fu *et al*., 2025).

Domain adaptation research has examined movement from controlled plant imagery to more complex disease images, including prior work working on uncertainty regularization and cross species representation. These experiments address a pertinent transfer issue; however, the predictive benchmark improvement is separate from prospective advisory gain. Transfer learning should be compared to training from scratch and reasonably equivalent local alternatives using target information (Xiang *et al*., 2026). Include consideration of labelling effort, computational cost, and adaptation time in the evaluation. Abstaining from using labelled target data has to be indicated, because it changes the feel of deployment. Arbitrary application of cross-domain modelling may lead to negative transfer if source relationships are inappropriate. Reporting unfavourable combinations helps establish operating boundaries and prevents selected successful transfers from being interpreted as universal portability across horticultural crops and production environments (Tunio *et al*., 2024).

6.3. Foundation Models and Biological Constraints

Self-supervised learning and foundation models have the potential to create general representations from many horticultural observations. By learning something useful before learning the full structure in task-specific annotation, they hold potential to improve situations in which labelled examples are difficult to come by with crop competence and evaluation data independence not depending on the model's size and the overall pretraining. Studies should provide all available information about sources of pretraining and assess the risk that benchmarks come from the public domain (Al Nahian *et al*., 2025). Multimodal systems require separate checks for image understanding, numerical reasoning, and text generation. A fluent explanation of a crop problem can appear convincing despite an incorrect diagnosis. Evaluation must therefore focus on grounded task performance, calibrated uncertainty, and verifiable recommendations rather than the apparent sophistication of the interface (Carneiro *et al*., 2025).

Process-informed models, integrating learned relationships with constraints derived from crop and environmental studies, enhance transfer. Water balance, energy exchange, growth dynamics, and nutrient cycling can inhibit implausible predictions. Still, mechanistic components are not automatically correct outside their calibration regime. Crop parameters, boundary conditions, and structural assumptions may still need to be tuned (Fasciolo *et al*., 2025). Hybrid approaches should be assessed against their separate components to determine whether integration brings robustness or merely added complexity. The most useful adaptation is the interpretable adoption: researchers must know what parameters have changed between crops and why. This enables the rationalization of transfer claims, making them more biologically plausible and signals the additional observations needed before uses in other production systems (Aderele *et al*., 2025).

7. DECISION-SUPPORT READINESS: TURNING INFORMATION INTO ACTION

7.1. Decision Definition and Uncertainty

Decision-support readiness begins with the precise definition of the decision to be supported. Identifying the user, action, spatial unit, timing, objective, and constraints first, before model selection, is what makes a system sound. An irrigation recommendation, for instance, must tell the user the amount and timing appropriate for the user equipment and crop development stage (Conde *et al*., 2024). A disease alert must indicate whether to inspect, sample, monitor, or consider intervention. The probability in raw form and it is a colour map might be useful information, but it is not a recommendation. Agronomic rules, economics and operations factor into the transition from prediction to action. This direct assessment tells us if better predictive performance actually makes changes in management that get understood, can be practiced and ultimately are useful for the user (Silvestri *et al*., 2025).

Uncertainty should influence the recommended action rather than appear only as a technical appendix. Prediction intervals, calibrated probabilities, and unfamiliar-input detection can help distinguish dependable recommendations from situations requiring additional observation (Agarwal *et al*., 2026). Their usefulness depends on whether uncertainty estimates remain informative under changing production conditions. A system may reasonably advise resampling when measurements conflict or defer to a grower when the crop lies outside its validated scope. Decision thresholds should reflect asymmetric consequences: missing an emerging outbreak may be more costly than requesting an unnecessary inspection, while unnecessary treatment can create other losses. Readiness therefore requires testing the complete uncertainty response, including abstention and escalation, against the costs and opportunities associated with actual management decisions (Farag *et al*., 2025).

7.2. Causal Reasoning and Readiness Assessment

Recommendations require evidence of reactions to action, not just evidence of association in past records. A model can discover that those blocks that went through heavy irrigation produce more yield because they are simply different soils and are managed better. This doesn't provide the benefit of having added water somewhere else. Prescriptive systems should differentiate forecasting in current practices from predicting outcomes under alternative interventions (Tanaka *et al*., 2024). This distinction may be aided with controlled experiments; ensure causal bases are met and validated process models. Similar worries are around reinforcement learning because it is more likely that in a learning environment the policy being sought may be optimized for unrealistic assumptions. Candidate policies should be checked for biological feasibility, constraint compliance, and performance in conditions that depart from the conditions used to develop or tune the simulation (Henningsen *et al*., 2026).

A readiness framework can synthesize evidence across data quality, capture of external validity, agronomic relevance,

operational reliability, economic value and governance. It should be a structured assessment though not a fruitlessly providing a numerical ranking. Capability. It may not be fit to autonomous operations, even if scoring high on prediction if it cannot detect sensor failure or respects equipment limits (Farajpour, 2026). Other requirements are tailored to failure mode and high-impact trades of control fit. Evidence on advisory scouting and automated fertigation should verify against different evidence thresholds. Strengths, gaps, and what comes next can be mapped across readiness profiles. This strategy allows the scaling decisions to be appropriate in the context, but be wary of the false precision of attempting to combine heterogeneous indicators into one universal maturity score (Ara *et al*., 2021).

Table 1. Framework for Evaluating AI Readiness in Precision Horticulture

Evaluation dimension	Key criteria	Validation approach	Readiness indicators	References
Data quality	Crop diversity, annotation accuracy	Assess data sources, sampling and labels	Representative, reliable datasets	Carraro *et al*., 2025; Mahin *et al*., 2025
Field validation	Environmental and production variability	Test across farms and seasons	Consistent field performance	Meyer & Pebesma (2022)
Cross-crop transfer	Species and cultivar adaptability	Test on unseen crops and environments	Effective transfer with documented adaptation requirements	Hu *et al*. (2025); Yang *et al*. (2024)
Predictive reliability	Data leakage, uncertainty, prediction errors	Independent testing and probability calibration	Reliable, uncertainty-aware predictions	Shrivastava *et al*. (2026); Bernett *et al*. (2024); Guo *et al*. (2017)
Decision support	Actionable agronomic recommendations	Compare AI with conventional management	Improved yield, resource efficiency and profitability	Cao *et al*. (2022); Hemming *et al*. (2020); van Laatum *et al*. (2026)
Operational readiness	Connectivity, sensor reliability, fault recovery	Test under realistic disruptions	Reliable operation with human oversight	Nyeki (2026); Bayar *et al*. (2025)
Responsible deployment	Costs, adoption, accountability	Assess economics, usability and governance	Sustainable, trustworthy adoption	Duncan *et al*. (2026); Kroupova *et al*. (2025); Yeo & Keske (2024)

7.3. Infrastructure and Explainability

Operational reliability and explainability are essential for the effective deployment of artificial intelligence in precision horticulture. System performance depends on reliable sensor calibration, data transmission, storage, processing, and actuator communication, as interruptions or outdated measurements can compromise prediction accuracy and management decisions. Edge computing may improve responsiveness and reduce connectivity dependence, while cloud computing supports centralized analysis and model updates (Nsoh *et al*., 2024). Systems should therefore be evaluated under realistic operational disruptions, incorporating fault detection, recovery mechanisms, and manual controls to minimize risks associated with irrigation, climate regulation, and automated machinery (Shekarian *et al*., 2024). Explainable AI further supports informed decision-making by clarifying the relationships among observations, model assumptions, uncertainty, and recommended actions. Explanations should distinguish measured from inferred information and remain understandable to users with different levels of technical expertise. Ultimately, usability evaluations should determine whether explanations improve understanding, appropriate trust, error detection, and practical decision-making rather than merely increasing visual complexity (Pai *et al*., 2025).

8. ADOPTION, SUSTAINABILITY AND RESPONSIBLE DEPLOYMENT

8.1. Economic and Environmental Performance

Economic evaluation should consider the full cost of keeping a system fit for further production cycles. Purchasing the hardware is just one component, and installation, connectivity, calibration, subscriptions, labelling, fixing, training and downtime may have a significant effect on profits (Charlton *et al*., 2025). Often lead to optimised appearance, less input, more synchronised harvested, or avoidance of losses but do not double count benefits. Sensitivity analysis is required because crop prices, labour costs and utilization rates differ across enterprises. A technology that is profitable in a large greenhouse can be a non-starter for a small seasonal vegetable operation. Reporting break-even conditions and the distribution of returns is of greater value than reporting one payback metric built on a single set of high utilisation rates with high levels of annual use (Vargas *et al*., 2024).

Environmental performance has to be evaluated in isolation from financial return and technical merit. It might be possible to use less irrigation water per hectare, but if production is expanded the total water use may not be less, and lower fertilizer application may influence yield or move losses elsewhere. Moving resources towards more relevant outcomes: Resource use intensity of a single unit of marketable product (Kumar *et al*., 2024). Where they influence the choice they matter, whether its

energy needed for sensing, calculation, lighting, or climate control. Clear evaluation boundaries must be provided to avoid enhancing performance artificially through the omission of upstream or downstream burdens. Precision management offers opportunities for environmental benefit, but those benefits should be measured under the actual production strategy rather than assumed from the presence of intelligent technology (Ruder *et al*., 2026).

8.2. Grower Participation and Data Governance

The responsible integration of artificial intelligence in horticulture requires human-centred approaches and robust data governance. Farmers must balance technological recommendations with practical constraints involving labour availability, equipment, market conditions, and farm operations. Participatory design, user training, accessible interfaces, and reliable connectivity can enhance technology adoption while preserving farmers' decision-making autonomy (Boucher *et al*., 2024). Effective data governance should safeguard commercially sensitive production information through clearly defined agreements on data ownership, access, usage, security, and accountability. Although federated learning may reduce centralized data sharing, challenges related to privacy, interoperability, and data protection remain. Standardized data formats and clearly established responsibilities among growers, advisers, technology providers, and developers are essential for building transparent and trustworthy systems. Ultimately, successful implementation should prioritize informed decision-making, farmer autonomy, and measurable practical benefits rather than unquestioning reliance on algorithmic recommendations (Rouzky *et al*., 2025).

8.3. Maintaining Reliability After Deployment

Post-deployment monitoring is necessary because production systems and software both changes. New cultivars, altered pruning, sensor replacement, unusual weather, or revised market grades can reduce performance without an obvious equipment failure. Monitoring should discriminate changes in input distributions from known degradation in predictivity or decision quality (Hinder *et al*., 2024). Periodic ground truth collection is still required, because drift indicators cannot indicate error magnitude or direction. Model updates must be versioned and verified prior to implementation of changes in an operational system. The ability to provide audit and learning feedback on the historical recommendations and relevant inputs should also be maintained. Thus, deployment is a process of continual revalidation with defined responsibilities for maintenance, retraining, and decommissioning once performance is no longer sufficient for the intended use of the system (Amodio *et al*., 2026).

9. RESEARCH PRIORITIES AND EVIDENCE-SYNTHESIS REQUIREMENTS

A priority research agenda would be to involve coordinated experiments between crops, farms, seasons, and management conditions made using a common outcome definition. Rather than just increasing the number of images, partnerships can gather the contextual information needed to explain what leads to success or failure. Benchmarks with more realistic missing data, hard-to-see, and unusual conditions and management-action tasks (Weyler *et al*., 2024). Transfer evaluations should reveal what the target is and how costly it is to adapt, while prospective trials should appraise the recommendations against good practice. Reproducibility would be enhanced if open protocols, code, wherever possible, and carefully curated datasets were provided. Publishing shaky transfers and operational failures as well, because that is what you learn from in terms of when to deploy. Such infrastructure would make subsequent reviews more actionable, sidestepping duplicate experiments that don't address practice uncertainty (Krisnawijaya *et al*., 2025).

Evidence synthesis should preserve differences among applications instead of pooling incompatible performance metrics. Classification accuracy, fruit-count error, irrigation savings, and harvest success describe different outcomes and cannot form a meaningful universal effect estimate. Meta-analysis should be attempted only where tasks, comparators, measurement units, and study designs are sufficiently compatible. Otherwise, structured narrative synthesis and evidence maps can show where conclusions are supported and where uncertainty remains. Risk-of-bias judgments should consider sampling, leakage, reference quality, missing outcomes, comparator choice, and selective reporting. Sensitivity analyses should test whether conclusions change when weak or potentially duplicated studies are excluded. This approach gives more weight to credible design and relevant outcomes than to impressive numbers reported without adequate methodological context (Deeks *et al*., 2019).

10. INTERPRETATION AND LIMITATIONS

The evidence considered here shows a conditional interpretation of progress. Artificial intelligence shows a lot of potential in horticultural perception and a few on limited controlled production testing, but against this artificial intelligence has not yet overcome all the limitations presented by incongruent imagery, trial cropping architecture, and context of deployment (these examples show a lack of validation throughout the literature as the systematic corpus across the literature has not yet been aggregated (Bac *et al*., 2017)). The same concern goes for unanswered questions about research leadership, phase of publication maturity and cross-crop transfer rates from simply wanting from queries alone. The review thus represents an analytical rigour and the specification of research grounded translation needs. Training on the suggested database and evaluation of the claims would pave the way for these hypotheses to be empirically evaluated with a tangible, replicable evidence-base (Kapoor and Narayanan, 2023).

11. CONCLUSION

The transition from prediction to practice will demand the proper balance between computational ambition, biological diversity, and operational responsibility. Field validation must establish performance under the conditions where decisions

are made; cross-crop evaluation must reveal what transfers and what requires adaptation; and readiness assessment must connect recommendations with feasible actions and measurable consequences. No single framework can do all of the above. The best systems will pair math and data with realistic agriculture, explicit uncertainty, robust infrastructure, and experienced people behind them. What a similar standard means for research and publishing is obvious: separate what was demonstrated and what has been proposed, be transparent about limitations, and count progress when management practices objectively improve in a way that is justifiable and within the intended scope of use.

REFERENCES

1. Adabara, I., Sadiq, B. O., Shuaibu, A. N., Danjuma, Y. I., Anold, A., Joe, M., ... & Mugisha, B. (2026). AI-Enabled Smart and Precision Agriculture: Smart Sensors, IoT, Deep Learning, Computer Vision, and Decision Support: A Comprehensive Survey.
2. Aderele, M. O., Srivastava, A. K., Butterbach-Bahl, K., & Rahimi, J. (2025). Integrating machine learning with agroecosystem modelling: Current state and future challenges. *European Journal of Agronomy*, *168*, 127610.
3. Agarwal, M., Rafiq, K., Mehta, R., Abrahms, B., & Harchaoui, Z. (2026). Leveraging machine learning and accelerometry to classify animal behaviours with uncertainty. *Methods in Ecology and Evolution*, *17*(2), 567-584.
4. Ahmad, A., El Gamal, A., & Saraswat, D. (2023). Toward generalization of deep learning-based plant disease identification under controlled and field conditions. *IEEE Access*, *11*, 9042-9057.
5. Akter, T., Bhattacharya, T., Kim, J. H., Kim, M. S., Baek, I., Chan, D. E., & Cho, B. K. (2024). A comprehensive review of external quality measurements of fruits and vegetables using non-destructive sensing technologies. *Journal of Agriculture and Food Research*, *15*, 101068.
6. Al Nahian, M. J., Ghosh, T., Sheikhi, F., & Maleki, F. (2025, June). Agri-fm+: A self-supervised foundation model for agricultural vision. In *2025 IEEE/CVF conference on computer vision and pattern recognition workshops (CVPRW)* (pp. 5511-5523). IEEE.
7. Amodio, V. D., Aversano, L., Dentamaro, V., & Franchini, F. (2026). Deep Learning in Farming: A Systematic Evidence-Weighted Review of Applications, Validation Gaps, and Emerging Frontiers. *Big Data and Cognitive Computing*, *10*(8), 273.
8. Ara, I., Turner, L., Harrison, M. T., Monjardino, M., DeVoil, P., & Rodriguez, D. (2021). Application, adoption and opportunities for improving decision support systems in irrigated agriculture: A review. *Agricultural Water Management*, *257*, 107161.
9. Arad, B., Balendonck, J., Barth, R., Ben-Shahar, O., Edan, Y., Hellström, T., ... & van Tuijl, B. (2020). Development of a sweet pepper harvesting robot. *Journal of field robotics*, *37*(6), 1027-1039.
10. Bac, C. W., Hemming, J., Van Tuijl, B. A. J., Barth, R., Wais, E., & van Henten, E. J. (2017). Performance evaluation of a harvesting robot for sweet pepper. *Journal of Field Robotics*, *34*(6), 1123-1139.
11. Baiardi, A., Francia, M., Golfarelli, M., Papadopoulos, A. V., & Pasini, M. (2026). Prescriptive watering: Data-driven optimization of water consumption in kiwifruit orchards. *Computers and Electronics in Agriculture*, *243*, 111306.
12. Bayar, J., Ali, N., Cao, Z., Ren, Y., & Dong, Y. (2025). Artificial intelligence of things (AIoT) for precision agriculture: Applications in smart irrigation, nutrient and pest management. *Smart Agricultural Technology*, 101629.
13. Benfenati, D., Amalfitano, D., Russo, C., Tommasino, C., & Rinaldi, A. M. (2025). Data centric Artificial Intelligence for agrifood domain: A systematic mapping study. *Computers and Electronics in Agriculture*, *239*, 110847.
14. Bernett, J., Blumenthal, D. B., Grimm, D. G., Haselbeck, F., Joeres, R., Kalinina, O. V., & List, M. (2024). Guiding questions to avoid data leakage in biological machine learning applications. *Nature Methods*, *21*(8), 1444-1453.
15. Bounajra, A., El Guemmat, K., Mansouri, K., & Akef, F. (2024). Towards efficient irrigation management at field scale using new technologies: A systematic literature review. *Agricultural Water Management*, *295*, 108758.
16. Bramer, W. M., Rethlefsen, M. L., Kleijnen, J., & Franco, O. H. (2017). Optimal database combinations for literature searches in systematic reviews: a prospective exploratory study. *Systematic reviews*, *6*(1), 245.
17. Cao, X., Yao, Y., Li, L., Zhang, W., An, Z., Zhang, Z., ... & Luo, D. (2022, June). igrow: A smart agriculture solution to autonomous greenhouse control. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 36, No. 11, pp. 11837-11845).
18. Carneiro, G. A., Aubry, T. J., Cunha, A., Radeva, P., & Sousa, J. J. (2025). Progress in applications of self-supervised learning to computer vision in agriculture: A systematic review. *Computers and Electronics in Agriculture*, *239*, 111134.
19. Carraro, A., Saurio, G., & Marinello, F. (2025). Towards rigorous dataset quality standards for deep learning tasks in precision agriculture: A case study exploration. *Smart Agricultural Technology*, *10*, 100721.
20. Chansanam, W., Elmalech, A., Kanyacome, S., Luekhong, P., Iam-On, N., & Boongoen, T. (2026). Leakage-Aware Transfer Learning with Explainable AI and CPU-Efficient Deployment for Mango Leaf Disease Classification on the MangoLeafBD Benchmark. *Applied Sciences*, *16*(14), 6989.
21. Charlton, D., Devadoss, S., Gallardo, R. K., Luckstead, J., & Vougioukas, S. (2025). Economic viability of robotic fruit harvesters to reduce large seasonal labor demands: Analysis of Gala and Honeycrisp apples. *Journal of the Agricultural and Applied Economics Association*, *4*(1), 70-87.
22. Chaudhary, V., Kumar, M., Chaudhary, V., Kumar, R., & Chauhan, C. (2025). Artificial intelligence in sustainable horticultural production: a systematic review. *Discover Plants*, *2*(1), 372.
23. Chen, S., Liu, A., Tang, F., Hou, P., Lu, Y., & Yuan, P. (2025). A review of environmental control strategies and models

for modern agricultural greenhouses. *Sensors*, *25*(5), 1388.
24. Chuquimarca, L. E., Vintimilla, B. X., & Velastin, S. A. (2024). A review of external quality inspection for fruit grading using CNN models. *Artificial Intelligence in Agriculture*, *14*, 1-20.
25. Conde, G., Guzmán, S. M., & Athelly, A. (2024). Adaptive and predictive decision support system for irrigation scheduling: An approach integrating humans in the control loop. *Computers and Electronics in Agriculture*, *217*, 108640.
26. Deeks, J. J., Higgins, J. P., Altman, D. G., & Cochrane Statistical Methods Group. (2019). Analysing data and undertaking meta-analyses. *Cochrane handbook for systematic reviews of interventions*, 241-284.
27. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of business research*, *133*, 285-296.
28. Duncan, E., Ruder, S. L., KC, K. B., Wittman, H., & Fraser, E. (2026). The political economy of agricultural data governance: Farmer perspectives on trust in data sharing. *Journal of Rural Studies*, *123*, 104076.
29. Elings, A. N. N. E., Righini, I. S. A. B. E. L. L. A., de Zwart, H. F., Hemming, S. I. L. K. E., & Petropoulou, A. (2019, June). Remote control of greenhouse cucumber production with artificial intelligence-results from the first international autonomous challenge. In *VI International Symposium on Cucurbits 1294* (pp. 69-76).
30. Farag, M., Emam, A., Leonhardt, J., & Roscher, R. (2025). Enhancing decision support in crop production: Analyzing conformal prediction for uncertainty quantification. *Computers and Electronics in Agriculture*, *237*, 110559.
31. Farajpour, M. (2026). Current applications of artificial intelligence for advancing agriculture, sustainability and climate mitigation. *Discover Artificial Intelligence*, *6*(1), 1525.
32. Farjon, G., & Edan, Y. (2024). AgroCounters—a repository for counting objects in images in the agricultural domain by using deep-learning algorithms: framework and evaluation. *Computers and Electronics in Agriculture*, *222*, 108988.
33. Fasciolo, B., Grasso, N., Bruno, G., & Chiabert, P. (2025). Hybrid machine learning and physics-based model for estimating lettuce (Lactuca sativa) growth and resource consumption in aeroponic systems. *Scientific Reports*, *15*(1), 23063.
34. Fu, R., Han, J., Sun, Y., Wang, S., Al-Absi, M. A., Wang, X., & Sun, H. (2025). Robust crop disease detection using multi-domain data augmentation and isolated test-time adaptation. *Expert Systems with Applications*, *281*, 127324.
35. Fuentes, A., Yoon, S., Kim, T., & Park, D. S. (2021). Open set self and across domain adaptation for tomato disease recognition with deep learning techniques. *Frontiers in Plant Science*, *12*, 758027.
36. Gao, X., Li, S., He, Y., Yang, Y., & Tian, Y. (2024). Spectrum imaging for phenotypic detection of greenhouse vegetables: A review. *Computers and Electronics in Agriculture*, *225*, 109346.
37. George, R., Thuseethan, S., Ragel, R. G., Mahendrakumaran, K., Nimishan, S., Wimalasooriya, C., & Alazab, M. (2025). Past, present and future of deep plant leaf disease recognition: A survey. *Computers and Electronics in Agriculture*, *234*, 110128.
38. Gong, L., Wang, W., Wang, T., & Liu, C. (2022). Robotic harvesting of the occluded fruits with a precise shape and position reconstruction approach. *Journal of Field Robotics*, *39*(1), 69-84.
39. Guo, C., Pleiss, G., Sun, Y., & Weinberger, K. Q. (2017, July). On calibration of modern neural networks. In *International conference on machine learning* (pp. 1321-1330). PMLR.
40. Hayat, A., Halder, S., Ghosh, S., Saha, A. K., & Karmakar, B. (2026). Deep Learning for In-Field Occlusion Handling and Real-Time Fruit Detection Under Dense Canopy Conditions. *Journal of Advance Agricultural Research*, *2*(2), 48-62.
41. Hemming, S., Righini, I., de Zwart, F., & Elings, A. (2019, June). Remote control of greenhouse cucumber production with artificial intelligence-results from the first international autonomous greenhouse challenge. In *International Symposium on Advanced Technologies and Management for Innovative Greenhouses: GreenSys2019 1296* (pp. 987-996).
42. Henningsen, A., Low, G., Wuepper, D., Dalhaus, T., Storm, H., Belay, D., & Hirsch, S. (2026). Estimating causal effects with observational data: guidelines for agricultural and applied economists. *Journal of Agricultural Economics*, *77*(2), 356-382.
43. Hinder, F., Vaquet, V., & Hammer, B. (2024). One or two things we know about concept drift—a survey on monitoring in evolving environments. Part A: detecting concept drift. *Frontiers in Artificial Intelligence*, *7*, 1330257.
44. Hossen, M. I., Awrangjeb, M., Pan, S., & Mamun, A. A. (2025). Transfer learning in agriculture: a review: MI Hossen *et al*. *Artificial Intelligence Review*, *58*(4), 97.
45. Hu, J., Li, J., & Wang, H. (2025). Cross-scale detection and cross-crop generalization verification of tomato diseases in complex agricultural environments. *Frontiers in Plant Science*, *16*, 1644271.
46. Ibnat, N., Azad, M. A. K., Chowdhury, S. S., Giordano, J. O., Adetunji, A. O., & Islam, S. (2026). Artificial intelligence in modern agriculture: recent advances, challenges, and future directions: a systematic review. *Artificial Intelligence in Agriculture*.
47. Jafar, A., Bibi, N., Naqvi, R. A., Sadeghi-Niaraki, A., & Jeong, D. (2024). Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. *Frontiers in Plant Science*, *15*, 1356260.
48. Jelali, M. (2024). Deep learning networks-based tomato disease and pest detection: a first review of research studies using real field datasets. *Frontiers in Plant Science*, *15*, 1493322.
49. Johanson, R., Wilms, C., Johannsen, O., & Frintrop, S. (2024, January). S 3 AD: Semi-supervised Small Apple Detection in Orchard Environments. In *2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)* (pp. 7061-7070). IEEE.
50. Johri, P., Kim, S., Dixit, K., Sharma, P., Kakkar, B., Kumar, Y., ... & Ijaz, M. F. (2024). Advanced deep transfer learning techniques for efficient detection of cotton plant diseases. *Frontiers in Plant Science*, *15*, 1441117.

51. Kapoor, S., & Narayanan, A. (2023). Leakage and the reproducibility crisis in machine-learning-based science. *Patterns*, *4*(9).
52. Kaur, R., & Watson, J. A. (2024). A scoping review of postharvest losses, supply chain management, and technology: implications for produce quality in developing countries. *Journal of the ASABE*, *67*(5), 1103-1131.
53. Krisnawijaya, N. N. K., Tekinerdogan, B., Catal, C., van der Tol, R., & Herdiyeni, Y. (2025). Implementing FAIR principles in data management systems: A multi-case study in precision farming. *Computers and Electronics in Agriculture*, *230*, 109855.
54. Kroupová, Z. Ž., Aulová, R., Rumánková, L., Bajan, B., Čechura, L., Šimek, P., & Jarolímek, J. (2025). Drivers and barriers to precision agriculture technology and digitalisation adoption: Meta-analysis of decision choice models. *Precision Agriculture*, *26*(1), 17.
55. Kumar, R., Bhardwaj, A., Singh, L. P., Singh, G., Kumar, A., & Pattnayak, K. C. (2024). Comparative life cycle assessment of environmental impacts and economic feasibility of tomato cultivation systems in northern plains of India. *Scientific Reports*, *14*(1), 7084.
56. Lehnert, C., McCool, C., Sa, I., & Perez, T. (2020). Performance improvements of a sweet pepper harvesting robot in protected cropping environments. *Journal of Field Robotics*, *37*(7), 1197-1223.
57. Mahin, M. A. N., Adnan, M. N., & Khondoker, R. (2025). Precision agriculture using machine learning and deep learning algorithms: a comprehensive study. *Res Sq*.
58. Maree, S. C., Zhang, P., van Marrewijk, B. M., de Zwart, F., Bijlaard, M., & Hemming, S. (2025). Autonomous greenhouse cultivation of dwarf tomato: Performance evaluation of intelligent algorithms for multiple-sensor feedback. *Sensors*, *25*(14), 4321.
59. Marzi, G., Balzano, M., Caputo, A., & Pellegrini, M. M. (2025). Guidelines for bibliometric-systematic literature reviews: 10 steps to combine analysis, synthesis and theory development. *International Journal of Management Reviews*, *27*(1), 81-103.
60. Meyer, H., & Pebesma, E. (2022). Machine learning-based global maps of ecological variables and the challenge of assessing them. *Nature Communications*, *13*(1), 2208.
61. Miranda, J. C., Gené-Mola, J., Zude-Sasse, M., Tsoulias, N., Escolà, A., Arnó, J., ... & Gregorio, E. (2023). Fruit sizing using AI: A review of methods and challenges. *Postharvest Biology and Technology*, *206*, 112587.
62. Moons, K. G., Damen, J. A., Kaul, T., Hooft, L., Navarro, C. A., Dhiman, P., ... & Van Smeden, M. (2025). PROBAST+ AI: an updated quality, risk of bias, and applicability assessment tool for prediction models using regression or artificial intelligence methods. *bmj*, *388*.
63. Moupojou, E., Tagne, A., Retraint, F., Tadonkemwa, A., Wilfried, D., Tapamo, H., & Nkenlifack, M. (2023). FieldPlant: A dataset of field plant images for plant disease detection and classification with deep learning. *Ieee Access*, *11*, 35398-35410.
64. Murphy, K. M., Ludwig, E., Gutierrez, J., & Gehan, M. A. (2024). Deep learning in image-based plant phenotyping. *Annual review of plant biology*, *75*(1), 771-795.
65. Najdenko, E., Lorenz, F., Dittert, K., & Olfs, H. W. (2024). Rapid in-field soil analysis of plant-available nutrients and pH for precision agriculture—A review. *Precision Agriculture*, *25*(6), 3189-3218.
66. Neupane, C., Pereira, M., Koirala, A., & Walsh, K. B. (2023). Fruit sizing in orchard: A review from caliper to machine vision with deep learning. *Sensors*, *23*(8), 3868.
67. Nikolaou, G., Neocleous, D., Christou, A., Kitta, E., & Katsoulas, N. (2020). Implementing sustainable irrigation in water-scarce regions under the impact of climate change. *Agronomy*, *10*(8), 1120.
68. Nsoh, B., Katimbo, A., Guo, H., Heeren, D. M., Nakabuye, H. N., Qiao, X., ... & Kiraga, S. (2024). Internet of things-based automated solutions utilizing machine learning for smart and real-time irrigation management: A review. *Sensors*, *24*(23), 7480.
69. Nyéki, A. (2026). Technical Limitations and Research Gaps of IoT and Big Data Infrastructures in Precision Crop Production: A Design-Oriented Review. *Agronomy*, *16*(14), 1354.
70. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*.
71. Pai, D. G., Balachandra, M., & Kamath, R. (2025). Explainable AI in agriculture: Review of applications, methodologies, and future directions. *Engineering Research Express*, *7*(3), 032202.
72. Pawera, L., Manickam, R., Wangungu, C., Bonnarith, U., Schreinemachers, P., & Ramasamy, S. (2024). Guidance on farmer participation in the design, testing and scaling of agricultural innovations. *Agricultural Systems*, *218*, 104006.
73. Polder, G., Dieleman, J. A., Hageraats, S., & Meinen, E. (2024). Imaging spectroscopy for monitoring the crop status of tomato plants. *Computers and Electronics in Agriculture*, *216*, 108504.
74. Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., & Koffel, J. B. (2021). PRISMA-S: an extension to the PRISMA statement for reporting literature searches in systematic reviews. *Systematic reviews*, *10*(1), 39.
75. Rouzky, R., Sarrafzadeh, A., Sowells-Boone, E., Pasandi, H. B., & Goins, G. (2025). Data governance in smart farming: A systematic review of challenges and gaps. *Information Processing in Agriculture*.
76. Ruder, S. L., Faxon, H. O., Orzel, E. C., Devkota, R., & Bronson, K. (2026). Reviewing the evidence on precision agriculture and environmental sustainability. *npj Sustainable Agriculture*, *4*(1), 9.

77. Sahar, R., Iqbal, J., Abid, M., & saad, E. (2026). From farm to society reshipping the future of food systems through green technologies, with a bibliometric and literature review for a future research agenda. *Discover Environment*, *4*(1), 246.
78. Scalisi, A., Plozza, T., Reddy, P., Peavey, M., McClymont, L., Rochfort, S., ... & Goodwin, I. (2024). Localised and tree total crop loads influence trunk growth, return fruit set, yield, and fruit quality in apples. *Horticulture Advances*, *2*(1), 17.
79. Shafay, M., Hassan, T., Owais, M., Hussain, I., Khawaja, S. G., Seneviratne, L., & Werghi, N. (2025). Recent advances in plant disease detection: challenges and opportunities. *Plant Methods*, *21*(1), 140.
80. Shawon, S. M., Niha, F. L., Sinan, O. H., Abed, M. J., Al Qwaid, M., Sarker, M. T., & Zubair, H. T. (2026). Integrating federated learning and explainable AI for plant disease detection: A systematic review of recent advances in precision agriculture. *International Journal of Computational Intelligence Systems*, *19*(1), 138.
81. Shekarian, S. M., Aminian, M., Fallah, A. M., & Moghaddam, V. A. (2024). AI-powered sensor fault detection for cost-effective smart greenhouses. *Computers and Electronics in Agriculture*, *224*, 109198.
82. Shrivastava, T., Agrawal, A. K., Shukla, A., & Dubey, P. (2026). An uncertainty-aware evaluation framework based on hierarchical vision transformers for robust cross-domain plant leaf disease classification. *Scientific Reports*.
83. Silvestri, R., Vecchio, M., Pincheira, M., & Antonelli, F. (2025). Smart Irrigation with Fuzzy Decision Support Systems in Trentino Vineyards. *Sensors*, *25*(23), 7188.
84. Tanaka, T. S., Heuvelink, G. B., Mieno, T., & Bullock, D. S. (2024). Can machine learning models provide accurate fertilizer recommendations. *Precision Agriculture*, *25*(4), 1839-1856.
85. Tunio, M. H., ping Li, J., Zeng, X., Ahmed, A., Shah, S. A., Shaikh, H. U., ... & Yahya, I. A. (2024). Advancing plant disease classification: A robust and generalized approach with transformer-fused convolution and Wasserstein domain adaptation. *Computers and Electronics in Agriculture*, *227*, 109574.
86. Valente, J. (2022). Imagery and a Deep Learning. *Artificial Intelligence Applications in Specialty Crops*, 53485356.
87. van Laatum, B., Msaad, S., van Henten, E. J., McAllister, R. D., & Boersma, S. (2026). Improving greenhouse fruit-production control by integrating reinforcement learning into short-horizon model predictive control. *arXiv preprint arXiv:2607.07365*.
88. Vargas, C., Gamache, S., Henao, N., Agbossou, K., & Nagarsheth, S. (2024). A comprehensive cost mapping of digital technologies in greenhouses. *Smart Agricultural Technology*, *9*, 100634.
89. Wang, Y., Khodadadzadeh, M., & Zurita-Milla, R. (2023). Spatial+: A new cross-validation method to evaluate geospatial machine learning models. *International Journal of Applied Earth Observation and Geoinformation*, *121*, 103364.
90. Weyler, J., Magistri, F., Marks, E., Chong, Y. L., Sodano, M., Roggiolani, G., ... & Behley, J. (2024). Phenobench: A large dataset and benchmarks for semantic image interpretation in the agricultural domain. *IEEE transactions on pattern analysis and machine intelligence*, *46*(12), 9583-9594.
91. Xiang, K., Shi, D., & Zhu, X. (2026). Quantifying the reliability gap in cross-domain plant disease classification: benchmarking the limited efficacy of standard mitigation techniques under controlled-to-field shift. *Frontiers in Plant Science*, *17*, 1826962.
92. Yang, S., Feng, Q., Zhang, J., Yang, W., Zhou, W., & Yan, W. (2024). From laboratory to field: cross-domain few-shot learning for crop disease identification in the field. *Frontiers in Plant Science*, *15*, 1434222.
93. Yeo, M. L., & Keske, C. M. (2024). From profitability to trust: Factors shaping digital agriculture adoption. *Frontiers in Sustainable Food Systems*, *8*, 1456991.
94. Yousaf, A., Kayvanfar, V., Mazzoni, A., & Elomri, A. (2023). Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions. *Frontiers in Sustainable Food Systems*, *6*, 1053921.
95. Zhang, X., Song, S., Guo, C., Han, X., Leng, Z., & Zhang, Y. (2026). Spectral Imaging and Autonomous Inspection Technologies for Nutrient Diagnosis of Protected Horticultural Crops: A Review. *Horticulturae*, *12*(9), 1124.